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Statistical tracking of tree-like tubular structures with efficient branching detection in 3D medical image data

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Abstract
The segmentation of tree-like tubular structures such as coronary arteries and airways is an essential step for many 3D medical imaging applications. Statistical tracking techniques for the extraction of elongated structures have received considerable attention in recent years due to their robustness against image noise and pathological changes. However, most tracking methods are limited to a specific application and do not support branching structures efficiently. In this work, we present a novel statistical tracking approach for the extraction of different types of tubular structures with ringlike cross-sections. Domain-specific knowledge is learned from training data sets and integrated into the tracking process by simple adaption of parameters. In addition, an efficient branching detection algorithm is presented. This approach was evaluated by extracting coronary arteries from 32 CTA data sets and distal airways from 20 CT scans. These data sets were provided by the organizers of the workshop ‘3D Segmentation in the Clinic: A Grand Challenge II-Coronary Artery Tracking (CAT08)’ and ‘Extraction of Airways from CT 2009 (EXACT’09)’. On average, 81.5% overlap and 0.51 mm accuracy for the tracking of coronary arteries were achieved. For the extraction of airway trees, 51.3% of the total tree length, 53.6% of the total number of branches and a 4.98% false positive rate were attained. In both experiments, our approach is comparable to state-of-the-art methods.

(Some figures may appear in colour only in the online journal)
1. Introduction

Blood vessels and airways perform vital tasks in the human body. Pathologies of these organs can cause severe health defects. According to a 2008 WHO report, coronary artery disease and chronic obstructive pulmonary disease are leading causes of death worldwide. For assessment of these diseases, modern 3D image modalities such as computer tomography (CT) and computer tomography angiography (CTA) are increasingly important in clinical practice. To quantify the pathological geometrical changes of blood vessels and airways, extraction of these structures from the 3D images is essential.

Several vascular segmentation techniques have been published in the literature. An excellent overview is given by Lesage et al (2009c). The simplest method is region growing (Boskamp et al 2004), a growing process that incrementally introduces voxels which fulfil a specific inclusion criterion. Region-growing-based algorithms are computationally efficient. Classic region-growing techniques are suitable for detecting highly contrasted vessels, but often leak into surrounding tissue if the vessels have low contrast or corrupted appearance due to pathological changes or noise.

Active contour can be used for the vascular segmentation method. This energy-minimizing model evolves a contour into the object boundaries with guidance from external and internal forces. External forces are derived from image information, while internal forces consist of contour geometry and regularity (McInerney and Terzopoulos 1996). The active contour technique provides a framework which allows the integration of different formulations of features and models.

While both region-growing and active contour approaches aim to detect vessel lumen, centerline-based techniques directly extract vessel centerlines. Given a starting and ending point, minimal path approaches (Avants and Williams 2000, Li and Yezzi 2007) extract the vessel centerline using a graph-based search algorithm. The underlying cost image is formulated to favor vessel structures. These techniques rely on a global optimization scheme and produce robust results even with corrupted image data.

The statistical tracking technique is another centerline-based approach. Given a starting point, vessels are reconstructed by incrementally fitting a geometrical and an appearance model to the image data. Different tracking schemes have been applied. Kalman filtering has been used by Behrens et al (2003) and Wörz and Rohr (2007) to estimate the initial states of the fitting procedure in each iteration. Due to their Gaussianity and linearity assumptions, pathological vessel segments cannot be tracked correctly.

In recent years, multiple hypothesis tracking techniques have received considerable attention due to their improved ability to deal with corrupted data and multiple anomalies. Particle filtering (Doucet et al 2000, Arulampalam et al 2002, Doucet and Johansen 2008), also known as the sequential Monte Carlo technique, presents recursive tracking schemes which can be used to estimate the Bayesian posterior distribution function (pdf) of a dynamic process with a set of discrete states. Particle filtering was first applied to vessel segmentation by Florin et al (2005, 2006). In this research, the likelihood estimation relies on a Gaussian mixture model, which describes the intensity distribution of both vessels and hyperintense areas caused by calcifications and stents. In Schaap et al (2007) study, vessel-related prior knowledge including information about radius changes, direction changes and intensity changes is integrated into the Bayesian estimation framework. Inspired by particle filtering, Lesage et al (2008) introduced a new sampling scheme for statistical tracking, which allows the use of a relatively low number of samples to ensure tracking robustness. To optimize tracking accuracy at vessel segments with strong bending, Zambal et al (2008) proposed a geometrical model with two concentric circles which are translated and scaled along the estimated vessel direction. Using
this model the likelihood is estimated with a contrast-based term. Statistical tracking offers promising results (Florin et al 2005, Schaap et al 2007, Lesage et al 2008, Zambal et al 2008), particularly in terms of robustness against pathologies, as these techniques are capable of tracking multiple hypotheses and are compatible with the use of sophisticated models during tracking.

One drawback of many published vessel tracking methods is that they focus on single vessel tracking (Schaap et al 2007, Lesage et al 2008, 2009b). Tracking algorithms that detect vessel branchings can be categorized into two classes: approaches which use clustering algorithms (Florin et al 2005) and approaches which search for branches by tracking them over several test steps (Zambal et al 2008). The clustering-based methods analyze the spatial distribution of all hypotheses in each iteration. If two or more clusters are built, a branching is detected. This technique has only limited usefulness: it successfully identifies the main coronary arteries (MCA) but not the small branchings located in the lower parts of the vessel tree (Florin et al 2005). The research by Zambal et al (2008) selects one branching candidate per iteration. After tracking a single vessel, all candidates are carefully investigated and further tracked in several additional steps. Tracking is then continued with the best branching candidate. Thus, this branching detection procedure is a greedy search process.

Another drawback of sophisticated methods for the segmentation of tubular structure is that they are usually limited to a specific domain (Lesage et al 2009c). To the authors’ knowledge, only two works have addressed general usability. Friman et al (2010) proposed a deterministic tracking approach. This method was evaluated on data sets of coronary arteries and liver vessels. Although it gives promising tracking results, this method requires many user interactions. Bauer et al (2009, 2010) presented a general concept for the extraction of tubular structures. The tubular structures are first detected using a tube detection filter. The extracted tube centerlines are then grouped and linked together to reconstruct the tree-like structure. Based on the general concept, methods are adapted for the specific domains, such as liver vessels (Bauer et al 2010) and airways (Bauer et al 2009). Domain-specific prior knowledge is formulated as hard constraints.

In this work, a trainable statistical tracking approach for the extraction of tree-like tubular structures with ringlike cross-sections is presented. In contrast to previous work, specific a priori knowledge about the structure is learned using training data sets and is integrated into the tracking process by the adaption of parameters into the tracking process. In addition, an efficient branching detection algorithm is presented. This algorithm is related to the work of Zambal et al (2008), but avoids the greedy search of branching candidates by using a branching metric.

The remainder of this paper is organized as follows: section 2 presents the statistical tracking approach for single branch extraction and branching detection in detail. Experiments for tracking of coronary arteries and distal airways are described in section 3. In section 4, the tracking results are reported and compared to state-of-the-art methods in the respective domain. These results are discussed in section 5. Finally, this paper is summarized with the conclusion in section 6.

2. Methods

We will first describe the general algorithms for tracking a single branch and branching detection. Both algorithms are then combined into the statistical tracking process, followed by domain-specific initialization and preprocessing.
2.1. Single branch tracking

The tracking of a single branch is accomplished using a recursive Bayesian tracking technique similar to the work of Florin et al. (2005), Schaap et al. (2007) and Zambal et al. (2008). From a given starting point inside a tubular structure, multiple hypotheses of the current branch segment are investigated. According to Bayes’ rule, the posterior probability of the given hypothesis is estimated using a priori knowledge and likelihood information. New hypotheses are created from a set of the most probable hypotheses. Upon successful propagation, the track with the maximal posterior probability is used to reconstruct the branch.

In the mathematical formulation, the hypothesis of a branch segment at iteration $t$ can be described by its position $p_t = (x_t, y_t, z_t)^T$, orientation $v_t = (\theta_t, \phi_t)^T$, radius $r_t$, and intensity $b_t$. Thus each branch segment is characterized by a state vector $x_t = (p_t, v_t, r_t, b_t)$. A branch configuration is described by $x_{0,t} \equiv \{x_0, ..., x_t\}$. Based on the observation $z_{0,t}$ of the image data from iteration 0 to $t$, the posterior distribution measuring the fitness of the state vector $x_{0,t}$ with the corresponding observation $z_{0,t}$ can be estimated using the recursive Bayes’ rule

$$p(x_{0,t}|z_{0,t}) \propto p(x_t|x_{t-1})p(z_t|x_t)p(x_{0,t-1}|z_{0,t-1}),$$

where $p(x_t|x_{t-1})$ denotes the prior probability and $p(z_t|x_t)$ the likelihood function (Schaap et al 2007).

2.1.1. Trainable a priori knowledge. The Bayesian estimation framework facilitates the integration of prior knowledge about the tubular structure into the tracking process. Using the reference centerlines from training data sets, distributions of radius changes and direction changes are modeled as prior knowledge. With the assumption that a new state vector $x_t$ only depends on its direct predecessor $x_{t-1}$, the transition prior to $x_t$ is formulated as

$$p(x_t|x_{t-1}) \propto p(r_t|r_{t-1})p(v_t|v_{t-1}),$$

where $r_t$ and $v_t$ describe the radius and direction of the cylindrical model at iteration $t$, respectively. The difference $\Delta r_t = r_t - r_{t-1}$ and angle $\alpha_t$ between $v_t$ and $v_{t-1}$ are calculated at each sample point extracted along the reference centerlines. The Gaussian distribution is assumed for radius changes $p(\Delta r) = N(\mu_r, \sigma_r)$ and direction changes $p(\Delta \alpha) = N(\mu_\alpha, \sigma_\alpha)$. Model variables $\mu$ and $\sigma$ are learned from the reference centerlines and can be easily updated using training data sets for different application domains. Because a branch usually decreases in size from the proximal to the distal point, two different standard deviations $\sigma_{r+}$ and $\sigma_{r-}$ are estimated for the positive and the negative radius changes.

2.1.2. Likelihood estimation. To assess the likelihood of a given hypothesis, a cylindrical geometrical model is used (see figure 1(a)). Uniformly distributed points are created at the outer edge of the cylinder’s cross-sections. Thus the cylindrical model can be represented with the point set $c = \{w_i^{|i|}|1 \leq i \leq n, 1 \leq j \leq m\}$ with $i$ and $j$ as the index of points in the cross-sectional and longitudinal direction and $m$ and $n$ as the maximal number of points in these two directions, respectively. Our likelihood function is based on a flux-based feature called minimal flux (Lesage et al 2009a)

$$\text{MFlux}(x_t) = \frac{2}{nm} \sum_{i=1}^n \sum_{j=1}^m \min \left( \langle \nabla I(w_i^{|i|}), u_j^{|i|}, \nabla I(w_i^{|i|+|j|}), u_j^{|i|+|j|} \rangle \right)$$

with $\nabla I(w_i^{|i|})$ as the gradient vector at point $w_i^{|i|}$, $u_j^{|i|} = \frac{p - w_i^{|i|}}{\|p - w_i^{|i|}\}$ as the inward radial direction (see figure 1(a)), and $\langle \rangle$ as the operator of scalar product. The pair $(w_i^{|i|}, w_i^{|i|+|j|})$ describes the
Figure 1. The cylindrical model (dotted line) and cross-sections of a vessel segment (white object). (a) The cylindrical model. (b) Cross-section of the cylindrical model on a branching segment. (c) Cross-section of the cylindrical model slightly translated.

diametrically opposed points for an even number \( n \) of points in a cylinder’s cross-section. The inward flux is maximal when the cylindrical model is aligned with the branch. The minimal flux penalizes the asymmetric contributions to the flux along cross-sections. It is used to reduce the high number of responses caused by large-scale hyperintense structures such as heart chambers (Lesage et al. 2009a). Based on the minimal flux, the likelihood function is defined as

\[
p(z_t | x_t) = P(M\text{Flux}(x_t))N(\mu_{It}, \sigma_{It})
\]

with \( P(l) = \frac{1}{1 + e^{-l}} \) as the sigmoid function. The term \( N(\mu_{It}, \sigma_{It}) \) ensures that the inner intensities of the cylindrical model resemble those of the tubular structure. In the case of the vessel tracking, this term prevents tube configurations from adapting to calcifications, which appear as hyperintense areas inside the vessel.

2.1.3. Termination conditions. The posterior pdf of a segment is used to recognize the end of a real branch. Low responses of the posterior pdf indicate limited similarity between the observed image data and the cylindrical model of a tubular structure. However, poor matching of the cylindrical model on pathological segments, such as stenosis, also causes low responses of the posterior pdf. To bridge the pathological locations while ensuring appropriate termination of a track, \( k \)-continuous state vectors \((x_0, \ldots, x_{k-1})\) are considered in each iteration. If the mean posterior pdf falls below the threshold \( T_p \), the tracking is stopped.

\[
\frac{1}{k} \sum_{i=0}^{k-1} \log p(x_i | z_i) < T_p.
\]

In addition, a branch should not intersect with itself. If the angle between the direction vector \( v_0 \) of state vector \( x_0 \) and direction vector \( v_k \) of state vector \( x_k \) exceeds the threshold \( T_a \), the tracking is also stopped.

2.2. Branching detection

The poor fit of the cylindrical model to branching segments is used to develop the branching detection algorithm. First, a branching metric is introduced. Next, all branching candidates are evaluated. Finally, the tracking is performed recursively with the next starting point.

2.2.1. Branching metric. To define the branching metric, the same cylindrical model as used for statistical tracking is applied. Due to the ellipsoidal geometry of branching segments, the
The cylindrical model is not able to fully match the structure. Despite the best possible match, there is still a side of the cylinder residing inside the hyperintense structure (see figure 1(b)). Therefore, the radial gradients receive low responses at the cylindrical surface on the side toward the branchings, and high responses on the side with the branch margins. By comparison, the cylindrical model usually fits a single branch quite well. The radial gradients on all sides of the cylinder demonstrate high responses. Thus, the side flux becomes a characteristic feature for branchings.

To formulate the side flux mathematically, the term ‘side’ is first introduced. A side is defined as a part of the cylindrical surface. It is as high as the cylinder in the longitudinal direction and forms an arched curve in the cylinder’s cross-section. Similar to the description of the cylindrical model, a side can be represented with a point set \( s_i = \{ w_{kj} | i + 1 \leq k \leq i + w_s, 1 \leq w_s < n, 1 \leq j \leq m \} \). \( k \) and \( j \) are indices of points in the cross-sectional and longitudinal direction of the cylinder, \( w_s \) and \( m \) are the maximal number of points in these two directions and \( i \) indicates the start position of the side. \( w_s \) and \( m \) can also be called the width and height of the side. The set of all sides of the cylinder with a certain width of \( w_s \) can be described with \( S = \{ s^i | 1 \leq i \leq n \} \). Based on the definition of side, the side flux can be formulated as

\[
S_{\text{Flux}}(x_t) = \min_{s_i \in S} \left( \frac{1}{w_s m} \sum_{k=i+1}^{i+w_s} \sum_{j=1}^{m} \langle \nabla I(w_{kj}^s), u_{kj}^s \rangle \right)
\]

with

\[
\tilde{s}_i = \arg \min_{s_i \in S} (S_{\text{Flux}}(x_t)).
\]

\( \nabla I(w_{kj}^s) \) denotes the gradient vector at point \( w_{kj}^s \), and \( u_{kj}^s \) the inward radial direction (see figure 1(a)). In practical cases, it is possible that the cylindrical model will not match the branch perfectly. In certain situations, slightly translated matchings can be observed (see figure 1(c)). This results in a low response of the side flux similar to that of branchings. To distinguish between them, the average intensity difference between the observed side \( s \) and the opposite side \( s^\pi \) of the cylindrical mesh is taken into account.

\[
D(s) = \frac{(I_s - I_{s^\pi})}{\sigma}
\]

where \( \sigma \) denotes the standard deviation of the intensity differences on all sides of the cylindrical model. This measure creates a high response in cases such as in figure 1(c) due to the asymmetric contribution of intensity, but a low response in cases such as figure 1(b). Combining the flux-based and intensity-based features, we define a branching metric as a conjunctive combination of (6) and (8):

\[
B(x_t) = S_{\text{Flux}}(x_t) D(\tilde{s}_i).
\]

When calculating this metric at each branch segment, branching candidates appear as local minima.

2.2.2. Detection procedure. After tracking of a single branch terminates, each branch segment is assessed according to the branching metric. If the responses of a segment fall below a threshold \( T_b \), this segment is recognized as a branching candidate. Note that not all branching candidates represent a real new tubular structure. Pathological segments, such as segments with aneurysm, could be detected as branching candidates. To avoid false positives, all candidates are evaluated further by a preliminary tracking of three steps. False positive branches are discarded. The remaining branches are investigated further if they are located outside of a tolerance region of the already-detected branches. This step ensures that the
tracking procedure finds only new branches, and does not follow an already-detected branch. All surviving branching candidates are sorted decreasingly according to the posterior pdf. The candidate with the maximal posterior pdf is chosen as a new starting point for further tracking.

2.3. Tree structure extraction

In the following, the described algorithms are summarized and combined to extract complete tree structures. First, a single branch is tracked using algorithm 1 (see figure 2(a)). If the termination conditions are fulfilled, branching candidates are sought according to algorithm 2. The candidate with the maximal posterior pdf is chosen as a new starting point (see figures 2(b) and 2(c)). The tracking of a new branch is performed with algorithm 1 again (see figure 2(d)). This recursive process is performed until all branching candidates are inspected or a predefined maximal branch number is achieved. As the final step, branches with extremely short lengths are considered false positives and removed from the tracking result.

Algorithm 1 Single Branch Tracking

1: Add start vector $x_0$ to stack.
2: If stack is not empty, select the state vector with the maximal posterior pdf for tracking a new branch, otherwise go to algorithm 2 step 1.
3: Generate the next states with the help of a set of uniformly distributed points on a half sphere.
4: Calculate for each state vector the transition prior according to formula 2.
5: Evaluate the fitness of the cylinder model at each state vector according to formula 4.
6: Calculate the posterior pdf for all state vectors. If the termination conditions are not fulfilled, start step 3 again with all surviving successions.
7: Prune the branches for which the number of segments is below the pruning threshold $T_{pr}$ and go to step 2.

Algorithm 2 Branching Detection

1: Search for branching candidates in the current branch using the metric defined in formula 9.
2: Evaluate branching candidates by performing $n$ test tracking steps.
3: Prune the surviving state vectors from the last tracking step which reside inside the detected branches.
4: Add the remaining state vectors as branching points to a stack and go to algorithm 1 step 2.
2.4. Domain-specific initialization and preprocessing

The described algorithms are generically usable for the extraction of various tubular structures with ringlike cross-sections. Two applications, the extraction of coronary arteries and distal airways, were investigated in this work.

The tracking of coronary arteries requires two starting points for its initialization: one inside the left coronary artery (LCA) and one inside the right coronary artery (RCA). The starting radii are set manually according to prior knowledge about the structure, and the starting directions are estimated by the analysis of vesselness using the Hessian matrix (Frangi et al 1998).

The tracking of small distal airways involves an initial segmentation of the trachea and proximal bronchi for its initialization. In this study, they are segmented with an adaptive region-growing algorithm. The threshold is chosen such that maximal tree length is achieved and no leakage occurs. From the leaves of the reconstructed airway trees, starting points for several tracking processes are generated automatically. The entire airway tree is finally extracted with a hybrid method that combines the statistical tracking approach with the adaptive region-growing algorithm. Both methods are based on a preprocessing step called the voxel classification model (Lo et al 2010). This model uses the $k$-nearest neighbor classifier to distinguish between airway and non-airway voxels. An initial feature set of local image descriptors is used for training this classifier. It includes spatial derivatives up to the second order, eigenvalues of the Hessian matrix, the determinant and trace of the Hessian matrix, the Frobenius norm of the Hessian matrix and combinations of Hessian eigenvalues that measure tube, plate and blobness. For a detailed description of this model, we refer to the work of Lo et al (2010).

3. Experiments

The algorithms described in the previous section were implemented in C++ and integrated in the free software platform MITK (Wolf et al 2005). The following two experiments were performed to evaluate these algorithms.

3.1. Tracking of coronary arteries

3.1.1. Data sets. Experiments were conducted on 32 CTA data sets of coronary arteries, which were provided by the organizers of the workshop ‘3D Segmentation in the Clinic: A Grand Challenge II—Coronary Artery Tracking (CAT08)’ (Schaap et al 2009). The images were acquired using 64-row and dual-source CT scanners. All data sets have a slice thickness of 0.4 mm and an in-plane voxel size ranging from 0.28 to 0.37 mm. The presence of calcium was scored as absent, modest, or severe. Based on the scoring, the data were divided equally into a training group of 8 (3 absent, 4 modest, 1 severe) and a test group of 24 (9 absent, 12 modest, 3 severe) data sets. Reference centerlines were produced by three medical experts. The reference centerlines contain four coronary arteries: the RCA, LAD, LCX and one side branch (SB). The centerlines of the training data sets are publicly available.

3.1.2. Parameter settings. Table 1 shows the default parameter settings divided into four groups: parameters for the cylindrical model, parameters for the tracking scheme, parameters for branching detection and parameters for the termination conditions.

3.1.3. Evaluation measures. The Rotterdam evaluation framework provides two measures to assess the tracking quality: overlap (OV) and accuracy (AI) (Schaap et al 2009). Both measures
### Table 1. Parameter values for tracking of coronary arteries and airway trees. Different parameter settings are separated by a semicolon as follows: 'coronary artery settings; airway settings'. Equal parameter values for both applications are listed only once. Parameters marked with ** are learned from the training data sets for both experiments, with * only for tracking of coronary arteries. The symbol '-' indicates an unused parameter.

<table>
<thead>
<tr>
<th>Group</th>
<th>Parameter</th>
<th>Setting</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cylindrical model</td>
<td>min. cross-sectional points $N_{\text{min}}$</td>
<td>8</td>
</tr>
<tr>
<td></td>
<td>min. number of cross-sections $M_{\text{min}}$</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>ratio $F$ between length and radius</td>
<td>0.5</td>
</tr>
<tr>
<td>Tracking scheme</td>
<td>num. of new positions $p_{i+1}$</td>
<td>73</td>
</tr>
<tr>
<td></td>
<td>maximal radius $r_{\text{max}}$</td>
<td>4.0; 6.0</td>
</tr>
<tr>
<td></td>
<td>minimal radius $r_{\text{min}}$</td>
<td>0.3; 0.2</td>
</tr>
<tr>
<td></td>
<td>radius offset $r_{\text{Of}}$</td>
<td>0.6</td>
</tr>
<tr>
<td></td>
<td>radius spacing $r_{\text{sp}}$</td>
<td>0.1</td>
</tr>
<tr>
<td></td>
<td>**mean of curvature $\mu_v$</td>
<td>0.0</td>
</tr>
<tr>
<td></td>
<td>**std. dev. of curvature $\sigma_v$</td>
<td>0.5; 0.52</td>
</tr>
<tr>
<td></td>
<td>**mean of radius changes $\mu_r$</td>
<td>0.0</td>
</tr>
<tr>
<td></td>
<td>**std. dev. of positive radius changes $\sigma_r^+$</td>
<td>0.2; 0.1</td>
</tr>
<tr>
<td></td>
<td>**std. dev. of negative radius changes $\sigma_r^-$</td>
<td>0.4</td>
</tr>
<tr>
<td></td>
<td>**mean of mean intensity changes $\mu_I$</td>
<td>0.0</td>
</tr>
<tr>
<td></td>
<td>**std. dev. of intensity changes $\sigma_I$</td>
<td>150; 200</td>
</tr>
<tr>
<td>Branching detection</td>
<td>num. of sides of cyl. model $n_s$</td>
<td>4</td>
</tr>
<tr>
<td></td>
<td>branching measure threshold $T_b$</td>
<td>0.5; 0.3</td>
</tr>
<tr>
<td></td>
<td>num. of test tracking steps $n$</td>
<td>3</td>
</tr>
<tr>
<td>Termination</td>
<td>pruning threshold $T_p$</td>
<td>15; –</td>
</tr>
<tr>
<td></td>
<td>*window size $k$</td>
<td>4; 10</td>
</tr>
<tr>
<td></td>
<td>*probability threshold $T_p$</td>
<td>–2.0; –3.0</td>
</tr>
<tr>
<td></td>
<td>*angle threshold $T_a$</td>
<td>–0.6; 0.0</td>
</tr>
</tbody>
</table>

are based on a point-to-point correspondence between the reference standard centerline and the centerline to be evaluated. Each point of the centerlines is assigned a label of true positive, false negative or false positive. A point on the reference standard is labeled as true positive (TPR$_{ov}$) if its distance to at least one of the connected points on the evaluated centerline is less than the annotated radius at this position, false negative (FN$_{ov}$) if not. A point on the centerline to be evaluated is labeled as true positive (TPM$_{ov}$) if it has a distance to at least one of the connected points on the reference standard centerline that is less than the radius at this location, false positive (FP$_{ov}$) if not. Based on this labeling, the overlap measure is defined as

$$\text{OV} = \frac{\|\text{TPM}_{ov}\| + \|\text{TPR}_{ov}\|}{\|\text{TPM}_{ov}\| + \|\text{TPR}_{ov}\| + \|\text{FN}_{ov}\| + \|\text{FP}_{ov}\|}$$  \hspace{1cm} (10)$$

with \(\|\|\) as cardinality of a set of points. While the overlap measure describes the ability of a method to track tubular structures, the accuracy measure represents the average distance between the reference standard centerline and the centerline to be evaluated. The accuracy at a given point $x$ of the reference standard centerline can be formulated as

$$\text{AI}(x) = \sqrt{\frac{1}{M} \sum_{i=1}^{M} (d(p_x(x), p'_m))^2}$$  \hspace{1cm} (11)$$

with $M$ as the number of correspondences that connect the point $p_x(x)$ on the reference standard centerline with a point $p'_m$ on the centerline detected by the method with a distance less than the annotated radius at the reference point. The accuracy measure is only calculated for the parts of the evaluated centerline that are inside of the vessel. The function $d(\cdot)$ denotes the Euclidean distance between two given points. To compare the extraction results of the method and of the observers, relative scores Score$_{ov}$ and Score$_{ai}$, that range from 0 to 100 points, can
Table 2. Evaluation measures for the extraction of airway trees.

<table>
<thead>
<tr>
<th>Measure</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Branch count</td>
<td>The number of correctly detected branches.</td>
</tr>
<tr>
<td>Branch detected</td>
<td>The fraction of correctly detected branches in comparison to the total number of branches.</td>
</tr>
<tr>
<td>Tree length</td>
<td>The sum of the length of all correctly detected branches.</td>
</tr>
<tr>
<td>Tree length detected</td>
<td>The fraction of correctly detected tree length in comparison to the total tree length in the reference.</td>
</tr>
<tr>
<td>Leakage count</td>
<td>The number of disconnected sources where leakage occurs.</td>
</tr>
<tr>
<td>Leakage volume</td>
<td>The volume of regions that are not marked as ‘correct’ in the reference.</td>
</tr>
<tr>
<td>False positive rate</td>
<td>The fraction of the extracted volume that is not ‘correct’ in comparison to the reference.</td>
</tr>
</tbody>
</table>

be calculated. For both scores, 100 points indicate a perfect result for the method. A score of 50 points means that the method performs similarly to the observer and a score of 0 points indicates a complete failure of the method. For a detailed description of evaluation measures and scores, we refer to the work of Schaap et al (2009).

To evaluate the branching detection, two measures are considered: true positive rate (TPR) and false positive rate (FPR). An extracted branch is marked as true positive if more than 50% of this branch represents a real vessel or as false positive otherwise. The proposed algorithm is able to detect a number of small branches that are not present in the reference data sets. These branches were further validated by a medical expert.

3.2. Tracking of airway trees

3.2.1. Data sets. Experiments were performed on data sets of the thorax which were provided by the organizers of the ‘Extraction of Airways from CT 2009 (EXACT’09)’ workshop (Lo et al 2009). The data sets include 20 test data and 20 training data. They were acquired on several different CT scanner models using various scan protocols and reconstruction parameters. Data sets included scan results from healthy volunteers as well as from patients with a pathology of airway and lung parenchyma. Reference solutions were generated based on 15 submitted segmentations which were evaluated by medical experts. Voxels of the segmentation are divided into four classes: correct, partly wrong, wrong and unknown. The reference segmentation represents an association of the correct voxels in all segmentations.

3.2.2. Parameter settings. All parameter settings are listed in table 1. Because the reference segmentation of the training data is not publicly available, parameters for a priori knowledge were learned from the initial segmentation using the region-growing algorithm. Parts of the trachea and main bronchi were excluded from the training process. Note that these settings are suboptimal because the small distal bronchi are rarely taken into account. Other parameters were determined empirically.

3.2.3. Evaluation measures. Segmentation results were assessed with the evaluation framework ‘Extraction of airways from CT’ (EXAT’09) (Lo et al 2009). The sensitivity and specificity of the tracking algorithm are demonstrated using seven performance measures: branch count, branch detected, tree length, tree length detected, leakage count, leakage volume and FPR (see table 2). These measures give an impression of how well the proposed method performs based on a reference standard. They also enable readers to compare the performance of the proposed approach with those that were evaluated in EXACT’09. Clinical reasons to consider these measures depend strictly on the clinical application and the environment where
Figure 3. Surface renderings of the detected vessel trees (in red) versus the reference vessel trees (in white). (a) Problematic result. (b) Average result. (c) Best result.

Table 3. Average tracking results of test data sets (TS), training data sets (TR) and ten selected pathological vessels (PV) according to accuracy (AI) and overlap (OV).

<table>
<thead>
<tr>
<th></th>
<th>TS Mean ± Std.dev (mm/%)</th>
<th>Score</th>
<th>TR Mean ± Std.dev (mm/%)</th>
<th>Score</th>
<th>PV Mean ± Std.dev (mm/%)</th>
<th>Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>AI</td>
<td>0.51 ± 0.12</td>
<td>25.1</td>
<td>0.47 ± 0.11</td>
<td>28.4</td>
<td>0.48 ± 0.16</td>
<td>30.2</td>
</tr>
<tr>
<td>OV</td>
<td>81.5 ± 14.3</td>
<td>45.5</td>
<td>85.3 ± 9.6</td>
<td>45.4</td>
<td>84.64 ± 21.36</td>
<td>43.3</td>
</tr>
</tbody>
</table>

the airway extraction method is used. For example, in a CT-guided bronchoscopy setting, if the software environment is designed such that it is easier to remove falsely detected branches than it is to add missed branches, one might prefer an extraction method that has high sensitivity (e.g. tree length detected) and low specificity (e.g. FPR) for airway segmentation.

4. Results

4.1. Tracking of coronary arteries

4.1.1. Tracking quality. Average quantitative tracking results of 24 test data sets, 8 training data sets and 10 pathological vessels are shown in table 3. The pathological vessels contain vessel segments with stenoses and with or without calcifications. Because the reference standard centerlines are necessary for the evaluation, these pathological vessels were selected from the training data sets only. Examples of reconstructed vessel trees are illustrated in figure 3. Reconstruction results of a pathological vessel are illustrated in figure 4. The ranking results of the proposed approach in comparison to other state-of-the-art methods are shown in figure 5.

4.1.2. Branching detection. The branching detection results demonstrated in this section were for the training data sets because they are the only ones for which the reference standard centerlines are publicly available. The maximal number of detected LCAs is set to 5 per data set. Twenty three of the 24 main branches of the LCAs were detected successfully. All eight SBs contained in the reference data sets were identified correctly. Furthermore, 16 additional SBs were detected by the method. All detected SBs are true positives. Detailed results are listed in table 4. Examples of the successful detection results are illustrated in figures 6(a)–(f). Figures 6(g) and (h) show a rotated slice view of the missing vessel and 3D surfaces of the detected vessel in comparison to the reference standard.
Figure 4. Tracking results of a vessel with stenosis and calcifications. (a) Slice view of the original image. (b) Reconstructed vessel of the reference standard (hatched area in green). (c) Reconstructed vessel of the tracking result (dotted area in red).

Figure 5. Ranking of our approach in comparison to other state-of-the-art approaches that were submitted to CAT08 (Schaap et al 2009). The methods are divided into three categories: automatic extraction, extraction with minimal user interaction and interactive extraction. Our approach belongs to the second category.
Figure 6. Rotated slice views of the branches and surface renderings of the detection results. (a) Branches with pathological changes. (b) Detection result. (c) Branches in a data set with low signal-to-noise ratio. (d) Detection result. (e) Branches with multiple branchings. (f) Detection result. (g) Branches with low contrast to the background. (h) The detected branch (in red) and the missing branch (in white).

Table 4. TPR and FPR of the branching detection results for MCA and SBs.

<table>
<thead>
<tr>
<th>No. of vessels in reference</th>
<th>No of vessels in result</th>
<th>TPR (%)</th>
<th>FPR (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>MCA</td>
<td>24</td>
<td>23</td>
<td>95.8%</td>
</tr>
<tr>
<td>SB</td>
<td>8</td>
<td>25</td>
<td>100%</td>
</tr>
</tbody>
</table>

Table 5. Results of the initial segmentation (first two lines) and the hybrid segmentation (last two lines).

<table>
<thead>
<tr>
<th>Branch detected (%)</th>
<th>Tree length (cm)</th>
<th>Length detected (%)</th>
<th>Leakage volume (mm³)</th>
<th>False positive rate (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>118.9</td>
<td>50.7</td>
<td>92.3</td>
<td>45.6</td>
</tr>
<tr>
<td>Std. dev.</td>
<td>49.9</td>
<td>10.5</td>
<td>44.1</td>
<td>10.7</td>
</tr>
<tr>
<td>Mean</td>
<td>126.5</td>
<td>53.6</td>
<td>104.5</td>
<td>51.3</td>
</tr>
<tr>
<td>Std. dev.</td>
<td>57.2</td>
<td>12.0</td>
<td>51.6</td>
<td>12.1</td>
</tr>
</tbody>
</table>

4.2. Tracking of airway trees

Table 5 demonstrates the average quantitative results on 20 test data sets. The initial and the hybrid segmentations of airway trees, that combine the region-growing approach with the statistical tracking, are compared with other state-of-the-art methods. Figure 7 shows the comparison results in terms of detected tree length versus FPR. Examples of reconstructed airway trees are shown in figure 8. In particular, segmentation results on distal bronchi are demonstrated on two data sets. Figures 9(a)–(d) show slice views of the hybrid segmentation in contrast to the initial segmentation for the extraction of distal bronchi. To analyze leakage, the surface renderings of two segmented airways using the hybrid algorithm are shown in figures 10(a)–(d). The first example demonstrates a common case of leakage with a FPR of 3.22%. The second example shows a poor segmentation with several leakages. Its FPR is 10.75%.
Figure 7. Detected tree length versus FPR of initial segmentation, hybrid segmentation and other state-of-the-art approaches that were submitted to EXACT’09 (Lo et al 2009).

Figure 8. Surface renderings of the initial segmentation results (in blue) and hybrid segmentation results (in red). (a) Problematic result (CASE 27). (b) Average result (CASE 30). (c) Best result (CASE 22).
5. Discussion

5.1. Tracking of coronary arteries

Table 3 shows that an average OV of 81.5% was achieved in the tracking of 24 test data sets. These results are comparable with the performance of the trained observers. Approximately 73% of the vessels were extracted with an overlap above 80%. This demonstrates that the proposed termination conditions are appropriate for most data sets. Early termination is the main cause of lower overlap. It occurs primarily in data sets with a signal-to-noise ratio which is significantly different from the training data sets. Taking the signal-to-noise ratio into account in the termination conditions could further improve the tracking results (Zambal et al 2008).

According to the accuracy measure, our approach performs only half as well as the trained observer. This was expected as the proposed tracking method does not include a refinement procedure, which corrects predicted positions in the propagation process. Integration of a recentering method into the tracking process, such as that presented by Zambal et al (2008), is a topic of future work. However, an average accuracy of 0.51 mm is sufficient for many applications including preoperative planning and visualization of vascular structures.

In considering the tracking results of the selected pathological vessels, the deterioration of OV with 0.66% and of AI with 0.01 mm compared to the average results on training data sets is almost negligible (see table 3). The large standard deviation of OV is due to early termination of the tracking by one pathological vessel. In most cases our approach is able to bridge over the vessel segments with stenoses. This is an advantage of the statistical tracking in contrast to the intensity-based region-growing approach: the latter could terminate earlier
or leak into surrounding tissue at pathological vessel segments. In figure 4, one may ask why the reconstructed surfaces do not show narrow parts at segments with stenoses. This is due to the proposed approach primarily generating centerline information as output. The surfaces in figure 4 represent only a rough segmentation of the vessels. Using the centerline information to generate an exact segmentation of the vessels is a topic of future work.

Table 4 shows that 95.8% of the MCA and all SBs in the reference standard of the training data sets can be detected correctly. The only missing branch has a low contrast to the surrounding tissue. In that area, another true positive branch was found instead of the missing branch (see figures 6(g) and (h)). Examples in figures 6(a)–(f) show that branchings even in regions with difficult conditions such as strong noise, pathological changes and multiple branchings can be extracted successfully.

The FPR is an important measure to consider in evaluating the extraction methods. However, this evaluation is currently not possible as the reference standard does not contain a complete coronary tree and the reference centerlines of the test data sets are not publicly available. Schaap et al (2009) noted that using the evaluation framework, fully automatic methods can obtain a high evaluation ranking despite many false positives. By contrast, the 0.0% FPR in table 4 emphasizes a valuable advantage of our approach, although the experiment was performed on training data sets only.

5.2. Tracking of airway trees

Table 5 shows that the hybrid segmentation method can extract on average more than 50% of the total tree length and more than 50% of the total branches with a FPR under 5%. Although there are many missing branches, it should be noted that no method is able to extract more than 60% of the total tree length with a FPR below 5%. Compared to 15 other submitted approaches, our method has relatively high detection rate (see figure 7).

The improvements made by the statistical tracking approach in detecting tree length may seem sparse at first glance. The initial segmentation using the appearance-model-based region-growing approach already includes five generations of the airway in most cases (see figure 8). The statistical tracking approach was applied mostly to extract distal bronchi. In comparison to proximal bronchi, distal airway has small branches. Thus, the average extended tree length of 12.2cm is a notable improvement (see figures 9(a) and (b)). In addition, new branches in distal airway can be detected using the proposed approach (see figures 9(c) and (d)).

Compared to the initial segmentation, the FPR of the hybrid segmentation increased from 2.35% to 4.69% on average. This increment of change is expected because the probability image, which is generated from the classification model, is quite noisy. The FPR could be reduced if additional features, such as the vessel orientation described in the research of Lo et al (2010), were taken into account in the likelihood estimation. Also note that the reference data do not include all true positive branches as they are defined as the union of all correctly segmented voxels of 15 submitted segmentations (Lo et al 2009). The additionally found branches are marked by the evaluation framework as false positive. However, some branches labeled as ‘false positives’ may be true positives according to manual inspection (see figures 10(a) and (b)).

The proposed tracking approach produced centerline information as output. As the evaluation tool supports only segmentation as input, the produced centerline was dilated for the evaluation. To obtain a more accurate segmentation of airways, more sophisticated methods are needed. Alternative approaches that have been proposed to accurately segment the airway walls given an initial estimate of the centerlines are Weinheimer et al (2008) and Petersen et al (2011).
5.3. Study limitations

The proposed tracking approach relies on a cylindrical geometrical model for both the extraction of a single branch and branch detection. This model assumption is less suitable for tubular structures with oval-like cross-sections like proximal bronchi. However, the smaller the tubular structure is, the more appropriate the cylindrical model becomes. Generally, smaller tubular structures are more difficult to extract. Our approach can be applied for tracking of different types of small tubular structures with ringlike cross-sections. Figures 5 and 7 show that in both tracking of coronary arteries and segmentation of distal bronchi, the proposed approach is comparable with other state-of-the-art methods that were submitted to the workshops CAT08 (Schaap et al 2009) or EXACT’09 (Lo et al 2009). The adaption of our approach for a specific application domain is mainly reduced to updating parameters. Out of the 22 parameters listed in table 1, seven are learned from the training data sets for both experiments. For the extraction of coronary arteries, the three parameters for the termination conditions are trained using the reference standard centerlines. Because the reference segmentations of airway trees are not publicly available, these three parameters had to set manually. Of the remaining parameters, eight are independent of the application domains. They are used to control the propagation process of the tracking and can be set globally for different application areas. The maximal and minimal radii of the tubular structure as well as the threshold for the detection of branchings are set manually for both experiments. Note that parameter settings in table 1 are used globally and not adapted for each data set. Further reduction of the parameter set and optimization of the parameter settings are ongoing. An alternative approach is the leave-N-out experiment.

The computation time to extract a coronary artery is approximately 45 s on a 6-core computer, which is acceptable for clinical use. Porting algorithms to GPU would further increase the computational performance.

6. Conclusion

This paper has presented a statistical tracking approach for the extraction of tree-like tubular structures. Domain-specific knowledge about the structure is learned from training data sets and integrated by parameter adaption into the tracking process. A branching metric based on a cylindrical model is used to improve detection efficiency. Experiments on data sets of coronary arteries and distal airways demonstrated that with a simple adaption, this statistical tracking approach is able to extract different types of tubular structures with ringlike cross-sections. In both application areas, the tracking results are comparable with other state-of-the-art methods.

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